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Research Article

Power-Aware Intelligent Water Drops Routing Algorithm for Best Path Selection in MANETs

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ABSTRACT

The absence of a central framework, the constantly fluctuating layout, the restricted resources, and the dispersed structure of Mobile Ad hoc Networks (MANETs), among other characteristics, make routing a critical problem. A proficient, energy-aware routing path selection algorithm can improve network performance. In this paper, a routing mechanism for path selection called the Power-aware Intelligent Water Drops Routing Algorithm (PIWDRA) is proposed, which is based on a physics-water metaheuristic called Intelligent Water Drops (IWD). In the algorithm, the global best path is selected based on a cost function that takes into consideration minimum energy, hop count, and time delay. Minimum energy has the highest weight factor. The link cost, Heuristic Undesirability (HUD), local update of the soil of a link and the soil of a drop, as well as the update of the soil of the paths that generated the local best path, incorporate one or more factors, which include time delay, energy, and the number of hops. Results obtained after simulating in Network Simulator 3 (NS-3) under variations in pause times and number of active sources show that the PIWDRA outperforms the Intelligent Water Drops Routing Algorithm (IWDRA), the Intelligent Water Drops-Based Optimization Algorithm for Mobile Ad-hoc Networks (IWDHocNet), the Ad-hoc On-Demand Distance Vector (AODV) routing protocol, and the Destination Sequence Distance Vector (DSDV) routing protocol. The performance metrics involved packet delivery ratio, average end-to-end delay, energy consumption, and network lifetime. In future work, the algorithm can be enhanced with congestion techniques such as cross-layer design, queue management, and rate control. Also, a hybrid metaheuristic routing algorithm can be the focus of future work.

Keywords: Intelligent Water Drops, Metaheuristics, Optimization, MANETs, Energy, Routing.

INTRODUCTION

Traditional wireless networks rely on fixed infrastructure, while alternatives like Mobile Ad hoc Networks (MANETs) are adaptable in challenging or inaccessible environments. MANETs are transitory networks that support connectivity among a collection of randomly located devices (nodes), which are wireless and do not rely on already existing infrastructure or centralised management [1]. The nodes found in MANETs can move freely at any time. As such, the network's topology can change quickly and suddenly. Also, nodes in the network act as not only sources but also routers, forwarding data to and from other nodes that cannot communicate directly [2].

The primary role of a typical routing algorithm in MANETs is to ensure the successful delivery of packets to their intended destinations. This is achieved by identifying a sequence of intermediate nodes that can forward the data from the source to the destination. A vast number of routing protocols have been proposed and are classified based on the transmission, power awareness, security, multipath, quality of service (QoS), geolocation, topology structure, and update mechanisms employed.

Power-aware routing protocols aim to address the energy efficiency problem in MANETs at different layers of the Open System Interconnection (OSI) reference model. Maximising battery efficiency is crucial for mobile nodes, as their active involvement depletes energy faster, potentially causing network partitioning and reducing the overall network lifespan. Among the eight groups of power-aware routing protocols is the metaheuristic-based approach, which is an enhancement over heuristic algorithms. The goal is to provide an effective algorithm that can produce fine and reasonable solutions for any routing optimization problem efficiently, reducing the computational burden.

This work proposes the Power-aware Intelligent Water Drops Routing Algorithm (PIWDRA), which is based on Intelligent Water Drops (IWD), a nature-inspired water metaheuristic algorithm that takes its inspiration from the drops of natural water that changes their environment to search for an almost optimum route to a destination, pond, or sea.

The Intelligent Water Drops (IWD), proposed by Dr Shah-Hosseini [3], is a nature-inspired water algorithm that takes its inspiration from the drops of natural water that change their environment to find an almost ideal route to a pond or sea. The basis for the IWD algorithm is the activities that occur between the water drops of a river and the river bed's soil (the water drops' environment). There is a relationship between water drops and their environment.

Figure 1. Flow of River Volta

Figure 1 shows the flow of the Volta River in Ghana. As depicted in the figure, the river path consists of bends and twists. The water drops can reach their destination even though their paths are not smooth. The paths taken by the water drops may not always be straight since there may be numerous kinds of limitations and impediments in reality. As they near their objective, they transition from their initial trajectory to a more optimal route in pursuit of the ultimate path. Water drops eventually change the river's course. Surprisingly, the river's pathway seems to be the best one given the surroundings' issues and distance to the target.

During its progression between two points in the river, a hypothetical water droplet undergoes three successive alterations [4]:

The speed of the water droplet rises.

The water droplet carries a larger amount of soil.

The soil level in the riverbed decreases between the two points.

The same functionality of a natural water drop can be achieved by creating an artificial water drop. This artificial water drop can be referred to as an IWD. The IWD algorithm creates IWDs with two primary properties [4], [5]:

The amount of soil it carries is soil (IWD).

The velocity that it possesses is called velocity (IWD).

As the IWD moves through the environment, these two properties vary. The river bed that will vary is the environment here. An environment is a representation of the problem that needs to be solved from an engineering standpoint.

The significant contribution of this study is as follows:

The strategy incorporates energy, hop count, and time delay factors that contribute to the network lifetime and packet delivery rate.

The global best path is selected based on a cost function that takes into consideration minimum energy, hop count, and time delay. Minimum energy has the highest weight factor.

The best path selection is achieved with minimum energy consumption.

The rest of the paper is organised as follows: Section 2 presents the related work on Intelligent Water Drops routing. Section 3 gives the proposed approach. The performance evaluation is provided in Section 4, while Section 5 gives the conclusions.

LITERATURE REVIEW

[6] addressed data aggregation challenges in heterogeneous Wireless Sensor Networks (WSNs) using the IWD algorithm. The study's system model encompassed stationary sensor nodes organised in an ad hoc arrangement across regions, exhibiting heterogeneity in initial energy, communication range, and sensing characteristics. The network consisted of sensor nodes, aggregator nodes, and a base station, with low-energy sensor nodes efficiently routing data through their high-energy counterparts for optimised energy consumption during transmission. The IWD algorithm was utilised to construct feasible data aggregation trees, and an enhanced version, IIWD, was introduced for improved velocity calculation. Energy was not factored into the IWD operations.

In [7], a control response was proposed that incorporates an IWD routing algorithm for Internet of Things (IoT) systems to enhance the traditional conventions of MANETs. However, the algorithm assumed the use of original IWD operations without energy considerations, and these operations were not explicitly defined.

In [8], the authors tackled the MultiPoint Relay (MPR) node separation problem resulting from mobility in VANETs. They proposed a cluster-based QoS-OLSR protocol with IWDs, addressing optimal MPR set selection, MPR disconnection, and failure management. By integrating QoS criteria such as connectivity, distance ratio, bandwidth, and velocity, the algorithm enhanced cluster head and MPR selection, improving the algorithm's exploration phase. The IWD-QoS-OLSR is built upon the IWD algorithm, incorporating speed and time for MPR selection, while energy was not considered.

Sensarma [9] proposed a routing algorithm in which QoS metrics such as delay, bandwidth, energy, buffer space, buffer size, and hop count were used by each packet with IWD properties in MANETs. The heuristic undesirability of an IWD's node selection was determined by QoS constraints and their associated weight factors. This reflected the respective importance of QoS parameters in soil and velocity updates. The path preference probability of each node was expressed, including some tuneable parameters that controlled the relative weights of the link soil and the constraints. Additionally, energy was considered part of the QoS constraints in the design of the algorithm. However, no evaluation was performed, and only intuitive analysis was provided.

In [10], the blend algorithm was proposed as a fusion of IWD and Ford-Fulkerson’s (FF) algorithm in VANETs. IWD was used to find the shortest path, while FF was used to find the non-augmenting optimal path during possible path iterations in global soil updating. The choice of the best vehicle was based on a probability function. An empirical function was defined for the problem, which measured the heuristic undesirability of a water drop traversing from one vehicle to another. The energy levels of the vehicles should have been considered in the global soil updating phase.

Sensarma and Majumder [11] used the IWD algorithm to create the Intelligent Water Drops Routing Algorithm (IWDRA), a multipath routing algorithm that prioritises the quality of service in MANETs. The primary difference between this paper and Sensarma's [8] work lies in the definition of data structures in Sensarma's later publication.

Khaleel and Ahmed [12] introduced a routing protocol for MANETs using IWD. This approach shared basic IWD features through simple packets to nearby nodes, even without knowing the network layout or links beforehand. The algorithm's standout feature was its ability to calculate different Relay Node Sets (RNS) and then use the IWD algorithm to choose the RNS with the fewest repeating nodes. The major downside of this exclusive MPR system was that the chosen relay nodes might not always be the optimal ones. Furthermore, the algorithm's design overlooked energy considerations. Additionally, updates from the RNS set-off nodes only factored in bandwidth availability. For the given problem, the undesirability heuristic was not specified.

Vaddhireddy [13] introduced the Intelligent Water Drops-Based Optimization Algorithm for Mobile Ad-hoc Networks (IWDHocNet), an IWD routing approach for MANETs. The link's cost was influenced by factors such as the length of the wait and the time since the last voyage. The Heuristic Undesirability (HUD) was defined to be based on queue length, and the soil of the IWD was based on only hop count. Energy was not considered part of any of the IWD operations defined in the work.

The literature understudied focuses on the use of IWD in routing path selection. The authors reviewed existing algorithms to inform the development of the proposed PIWDRA and also to compare those applied in MANETs, such as the IWDRA and the IWDHocNet with the proposed strategy.

METHODOLOGY

The algorithm starts with initialising parameters. Water drops are placed at starting nodes and construct paths by moving to adjacent nodes based on probabilities influenced by soil levels and link cost. Each water drop updates its velocity and reduces soil on visited paths. After constructing paths, local soil updates reflect the drops' experiences and global soil updates reinforce the best path found. This iterative process continues until stopping criteria are met, ultimately yielding the best path or solution.

Proposed Methodology of PIWDRA

Input: Graph $G = (V, E)$ and Drops

Output: Total best solution (TTB)

Step 1: Initialize static parameters:

The static parameters used in the algorithm are initialized.

The graph (V, E) representing the problem with VN number of nodes is provided for the algorithm.

At the start, the quality of TTB is set to the worst value, which is negative infinity, $q(T)^{TB} = -\infty$.

The algorithm halts when it reaches $iter_{max}$. The value of $iter_{max}$, the maximum number of iterations, is set by the user. The value is set to 100. $iter_{max} = 100$.

$iter_{count}$ counts the number of iterations. The value is set to zero. $iter_{count} = 0$.

The velocity updating parameters are set as $a_v = 10.00$, $b_v = 0.01$, and $c_v = 1$.

The soil updating parameters are set as $a_s = 10.00$, $b_s = 0.01$, and $c_s = 1$.

Each link to a nearby node is given a starting amount of soil. $InitSoil = 10000$.

The initial velocity of the originating Drop is set to 200. $InitVel = 200$.

N_{Drop}, the number of Drops, is set to equal the number of nodes in the graph. N_{Drop} is usually set to a positive number. $N_{Drop} = 250$.

ε_s is a small positive number to prevent division by zero. $\varepsilon_s = 1.0$.

ρ^{Drop}, the global soil updating parameter is set to 0.9. $\rho^{Drop} = 0.9$.

ρ_n, the local soil updating parameter is set to 0.9. $\rho_n = 0.9$.

Step 2: Initialize dynamic parameters:

The dynamic parameters used in the algorithm are initialized.

A visited node list, V_cDrop, is assigned to every Drop and set to empty. $V_c\text{Drop} = \{\}$

InitVel is set as the velocity of each Drop.

A zero amount of soil is set for all Drops.

Step 3: At regular intervals, a Drop is launched from every node s to find a path to a randomly selected destination node, d. Drops are small packets that serve as control packets and only serve to establish a path.

Step 4: Any launched Drop travels hop by hop to find a path to the destination node. While travelling, the Drops update their memory with the address of each visited node V_c as well as the time it took to arrive at the node.

Step 5: Steps 5.1 to 5.4 are repeated for those Drops with partial solutions.

5.1: At each node i, the Drop selects the next hop neighbour, j, from its neighbour list, which does not violate any constraints of the problem and ignores nodes that have already been visited. Nodejis selected probabilistically, taking into account the soil level present on the link connecting i and j, along with the link's cost. Based on Eq. (2), the probability is calculated.

$$prob(i, j;\ Drop) = \frac{f(soil(i, j))}{\sum_{k \neq V_{c\,(Drop)}} f(soil(i, k))} \quad (2)$$

The parameter $f(soil(i, j))$ in Eq. (2), which is defined in Eq. (3), specifies how good the path is. The function $g(soil(i, j))$ is used to shift the $soil(i, j)$ values to prevent any cancellation of the positive and negative numbers, and $cost(i, j)$ represents the cost of the link connecting i and j, which in this algorithm is computed using Eq. (4).

$$f(soil(i, j)) = \frac{1}{\varepsilon_s + g(soil(i, j)) + cost(i, j)} \tag{3}$$

$$cost(i, j) = \sigma \times TD + \mu \times \frac{1}{Min(E)} + \tau \times \frac{1}{N_{Hops}} \tag{4}$$

Where $\sigma = 0.02$, $\mu = 0.06$, and $\tau = 0.02$.

Information such as the time delay for the Drop to get to j from node i, TD, the minimum energy of the nodes in route, $Min(E)$, and the number of hops, $N_{Hops}$are all taken into account when calculating the cost of the link, cost (i, j), as outlined in Eq. (4). σ, τ, and μ are constant parameters to determine respectively, the weight of TD, $Min(E)$, and N_{Hops} in the function.

$$g(soil(i, j)) = \begin{cases} soil(i, j) \text{ if } \min(soil(i, j)) \geq 0 \\ soil(i, j) - \min(soil(i, l)) \text{ else} \end{cases} \tag{5}$$

5.2: The velocity with which the Drop moves is updated based on Eq. (6). The updated velocity is $vel^{Drop}(t + 1)$ and the old velocity is $vel^{Drop}(t)$; a_v, b_v, and c_v values are the static velocity updating parameters explained at the start of the algorithm.

$$vel^{Drop}(t + 1) = vel^{Drop}(t) + \frac{a_v}{b_v + c_v . soil^2(i, j)} \tag{6}$$

5.3: The amount of soil on the links along the discovered path is updated using Eq. (7). Heuristic undesirability, HUD, is defined for the given problem in Eq. (9).

$$\Delta soil(i, j) = \frac{a_s}{b_s + c_s . time^2(i, j; vel^{Drop}(t+1))} \tag{7}$$

Such that,

$$time(i, j; vel^{Drop}(t + 1)) = \frac{HUD(j)}{vel^{Drop}(t+1)} \tag{8}$$

$$HUD(i, j) = \frac{TD(i, j)}{E(j)} \tag{9}$$

5.4: The soil of the path from node i to j, as well as the soil carried by the Drop, $soil^{Drop}$, are both updated respectively, using Eqs. (10) and (11). In Eq. (10), ρ_n is a local soil updating parameter and N_{Hops} is the number of hops taken by the Drop to reach the destination d via node j; if the number of hops is greater, very little soil is removed from the link; this is done to make the amount of soil displaced inversely proportional to the number of hops so that more routes with fewer hops can be found. The notation $E(j)$ represents the energy level of j.

$$soil(i, j) = (1 - \rho_n). soil(i, j) - \rho_n . \frac{\Delta soil(i, j)}{N_{Hops} . E} \tag{10}$$

$$soil^{Drop} = soil^{Drop} + \frac{\Delta soil(i, j)}{N_{Hops} . E} \tag{11}$$

Step 6: The iteration best solution, TIB from all the solutions TDrop is found with Eq. (12).

In the algorithm, each Drop is generated at a starting node and then progresses through subsequent nodes until it reaches the end of the solution. To evaluate the fitness of the solutions, a fitness or quality function is required to measure the quality of each solution. The purpose of using a fitness function is to increase the likelihood of finding the TTB while also improving the algorithm's convergence rate. By calculating the cost of the path traversed by each drop during iterations, the fitness function ranks the individual solutions and identifies the solution with the minimum cost as the best solution. The path formed by the solution is checked to see if it is optimal or not based on the objective function, which is the cost function provided in Eq. (4). Time delay (TD), minimum energy ($Min(E)$), and the number of hops (NHops) are derived from the path's nodes. Concerning $Min(E)$, the routing algorithm should select a path that has the maximum value of the minimum energy that a node has in a path across all the possible paths.

$$T^{IB} = \arg\min \forall T^{Drop} cost(i, j) \tag{12}$$

Where each solution is denoted as T^{Drop}.

Step 7: The soils of the paths that created the present TIB are updated with Eq. (13).

$$soil(i, j) = (1 + \rho_{Drop}). \frac{soil(i, j)}{N_{Hops} . E} - \rho_{Drop} . \frac{1}{q(T^{IB})} . soil_{IB}^{Drop} \ \forall (i, j) \in T^{IB} \tag{13}$$

Where $soil_{IB}^{Drop}$ denotes the soil of the iteration-best solution Drop. By incorporating the best-iteration solution into the soil of the next iteration, the algorithm reinforces those good solutions, allowing the Drops to focus their search on promising areas in the hope of finding the best solution.

Step 8: TTB is updated by the current TIB using Eq. (14) at the end of each iteration of the algorithm.

$$TTB = \begin{cases} T^{TB} & \text{if } q(T^{TB}) \geq q(T^{IB}) \\ T^{IB} & otherwise \end{cases} \tag{14}$$

Step 9: The iteration counter is increased by 1, iter count= iter count+1. Step 2 is implemented if itercount< itermax

Step 10: TTB is produced, and the algorithm ends.

The flowchart of PIWDRA is provided in Figure 2.

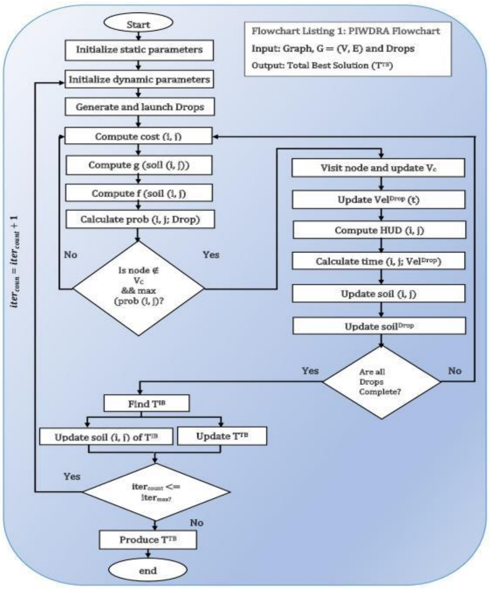

Figure 2. Flowchart of PIWDRA

Method of Simulation

PIWDRA is validated through the NS 3.37 simulator to compare its performance with the Intelligent Water Drops Routing Algorithm (IWDRA), the Intelligent Water Drops-Based Optimization Algorithm for Mobile Ad-hoc Networks (IWDHocNet), the Ad-hoc On-Demand Distance Vector (AODV) routing protocol, and the Destination Sequence Distance Vector (DSDV) by taking into consideration the following simulation parameters: Terrain dimension is 1500x1500 square metres, maximum node speed is 10 metres per second, size of a data packet is 512 bytes, size of a control packet is 8 bytes, type of traffic is constant bit rate (CBR), radio propagation model is two-ray ground reflection model, MAC protocol is IEEE 802.11, initial node energy is 100 joules, bandwidth is 11 megabits per second, transmission power is 3 watts, receiving power is 1.5 watts, sleep power is 0.6 watts, idle power is 0.05 watts, default transmission range is 250 metres, simulation time is 1500 seconds, queue type is dropped tail primary queue, queue length is 50 data packets, antenna model is omni direction.

The comparison is done in two scenarios. The first scenario involves varying pause times from 0 seconds to 200 seconds using a time interval of 40 seconds. The second scenario involves changing the number of active sources and data sessions to simulate different traffic load situations. These scenarios range from 10/15 (sources/connections) to 60/80, with intermediate values such as 20/25, 30/45, 40/60, and 50/80. A sufficient number of active source nodes are randomly selected to create low (10–20), medium (30–40), and high (50–60) levels of traffic. Table 1 provides the average performance results.

Performance Metrics

Packet Delivery Ratio (PDR): This is defined as the number of data packets received by the destination divided by the number of data packets transmitted [14].

Average End-to-End Delay (AE2ED): This is defined as the delay of a packet from the time it is transmitted by the sender node to the time it is received by the destination node [15].

Energy Consumption (EC): This is defined as the total energy utilised by the network entities during the period of the experiment [16].

Network Lifetime (NL): The time between when the network is launched and the first node dies due to battery exhaustion [17].

RESULTS AND DISCUSSION

Scenario 1: Impact of the Pause Times Variation

Packet Delivery Ratio

Figure 3 displays the graph of the packet delivery ratio against varying pause times. The results indicate that PIWDRA outperformed all the other strategies. The improvement rates (IR) (in percent) of PIWDRA over IWDRA, IWDHocNet, AODV, and DSDV are 1.52, 7.16, 17.49, and 24.52, respectively. PIWDRA is not significantly affected by pause time variations since its average performance is 92.90 percent. The performance of PIWDRA decreases slightly as the network becomes less dynamic (i.e., from 0 to 80 pause times) and then increases moderately until the network becomes static.

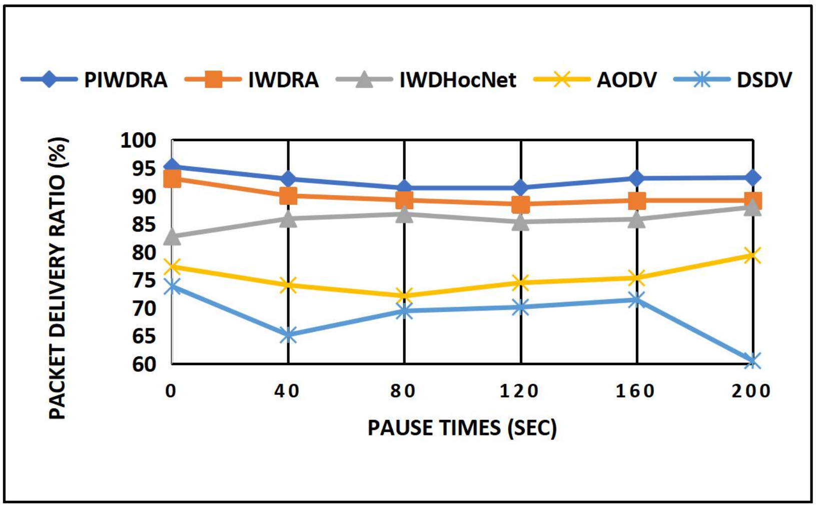

Figure 3. Packet Delivery Ratio Under Various Pause Times

Average End-to-End Delay

Figure 4 shows the relationship between AE2ED and different pause times. PIWDRA had the best average performance of 0.15 seconds, while DSDV had the lowest average performance of 0.31 seconds. The IR (in seconds) of PIWDRA over IWDRA, IWDHocNet, AODV, and DSDV are 0.02, 0.06, 0.08, and 0.16, respectively. The highest delay performance of 0.13 seconds occurred with PIWDRA at 0 seconds and 200 seconds pause times, while the least delay performance of 0.45 seconds occurred with DSDV at 0 seconds pause time. Even though the delay of DSDV continued to decrease sharply as the paused times were increased, it showed the least performance.

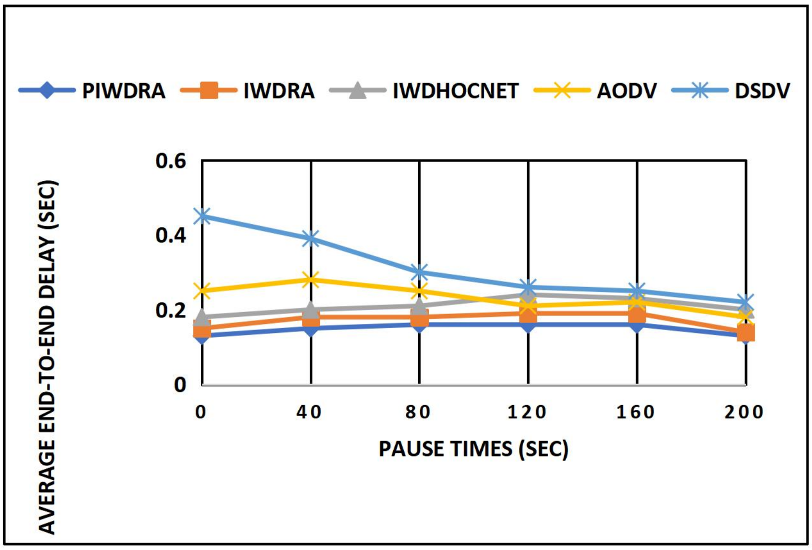

Figure 4. Average End-to-End Delay Under Various Pause Times

Energy Consumption

Figure 5 shows the link between energy consumption and varying pause times. PIWDRA had the highest performance of 27.87 joules, while DSDV had the lowest performance of 55.25 joules. The IR (in joules) of PIWDRA over IWDRA, IWDHocNet, AODV, and DSDV are 4.35, 10.37, 23.68, and 27.38, respectively. The highest performance of 22.11 joules occurred with PIWDRA when the pause time stood at 0 seconds, while the lowest performance of 60.8 joules occurred with DSDV when the pause time stood at 200 seconds. PIWDRA demonstrated consistent and steady performance while consuming significantly less energy than all the other strategies.

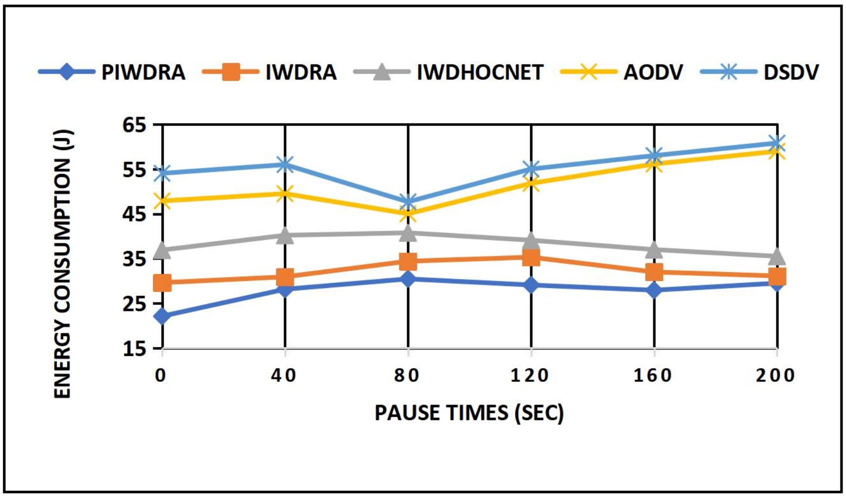

Figure 5. Energy Consumption Under Various Pause Times

Network Lifetime

Figure 6 displays the relationship between network lifetime and varying pause times. PIWDRA had the best average performance of 535.51 seconds, while DSDV had the lowest average performance of 308.29 seconds. The IR (in seconds) of PIWDRA over IWDRA, IWDHocNet, AODV, and DSDV are 50.34, 92.22, 146.52, and 227.22, respectively. PIWDRA exhibited the maximum NL of 660.28 seconds when the network became static, while DSDV had the lowest performance of 261.89 seconds under the same condition. The performances increased steeply for PIWDRA when the pause times increased from 120 to 200 seconds. This suggests that the new algorithm is also suited to handle longer periods of network inactivity.

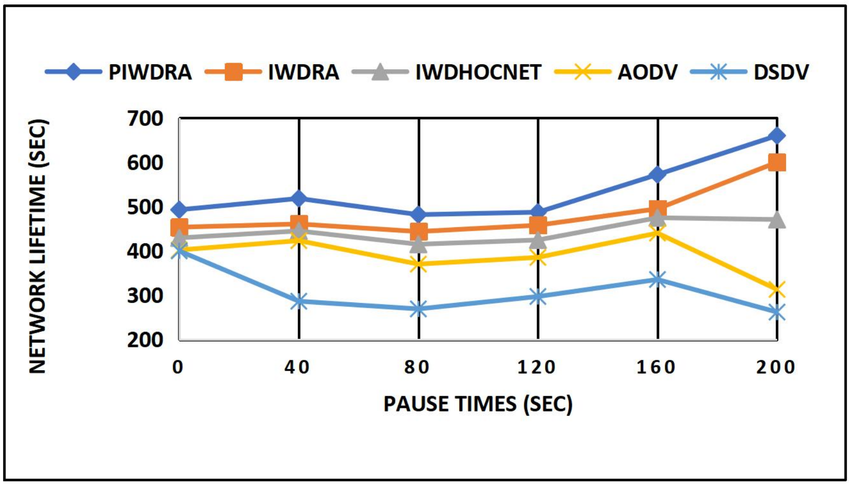

Figure 6. Network Lifetime Under Various Pause Times

Scenario 2: Impact of Varying Network Traffic Load

Packet Delivery Ratio

Figure 7 illustrates the link between PDR and the varying number of active sources. PIWDRA outperformed all others with an average PDR of 99.33 percent, while DSDV had the lowest average PDR of 97.83 percent. The IR (in percent) of PIWDRA over IWDRA, IWDHocNet, AODV, and DSDV are 0.15, 0.65, 1.03, and 1.49, respectively. The highest performance of 99.83 percent occurred with PIWDRA with 10 sources, while the lowest performance of 97.21 percent occurred with DSDV with 30 sources. The PDRs for PIWDRA consistently stayed above 99 percent, with only one record in the range of 98 percent, indicating the algorithm's superior performance compared to the others.

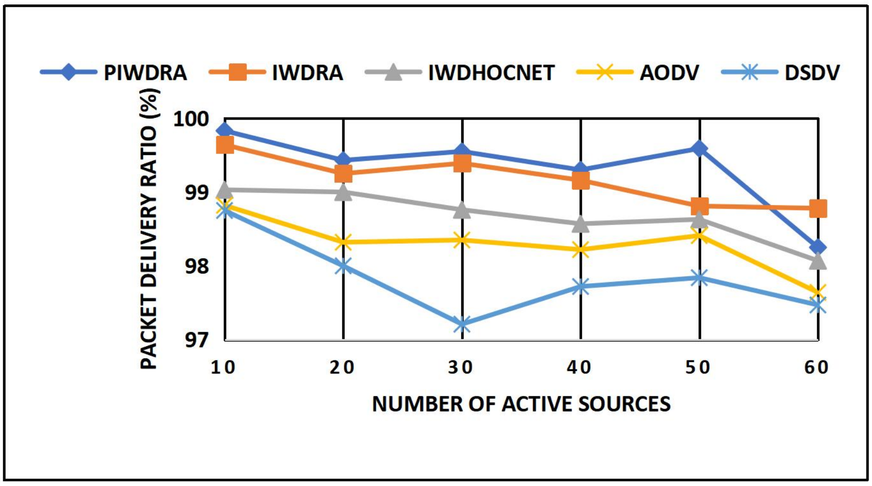

Figure 7. Packet Delivery Ratio Under Various Number of Active Sources

Average End-to-End Delay

Figure 8 depicts the relationship between AE2ED and the varying number of active sources. PIWDRA had the highest average delay performance of 0.14 seconds, while DSDV lags at 0.31 seconds. The IR (in seconds) of PIWDRA over IWDRA, IWDHocNet, AODV, and DSDV are 0.14, 0.19, 0.24, 0.27, and 0.31, respectively. The optimum delay performance of 0.09 seconds occurred with PIWDRA with 10 sources, while the lowest performance of 0.48 seconds occurred with DSDV with 60 sources. The performance of all five routing algorithms declined as the number of sources increased, with DSDV experiencing a more significant effect than all the others.

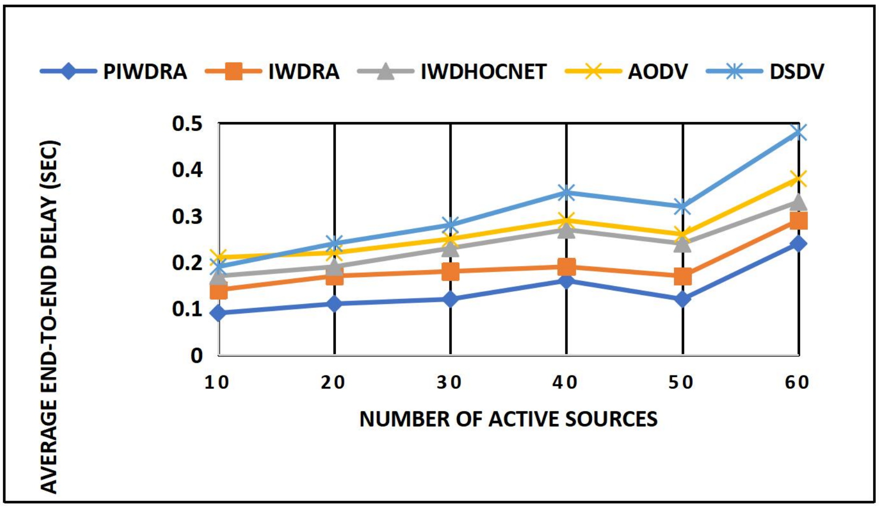

Figure 8. Average End-to-End Delay Under Various Number of Active Sources

Energy Consumption

Figure 9 depicts the correlation between energy consumption and variations in the number of active sources. PIWDRA had the highest average performance of 50.96 joules, while DSDV had the lowest average performance of 68.49 joules. The IR (in joules) of PIWDRA over IWDRA, IWDHocNet, AODV, and DSDV are 50.96, 55.02, 60.92, 64.26, and 68.49, respectively. The lowest EC of 48.1 joules occurred with PIWDRA at 60 sources, and the highest EC of 74.05 joules occurred with DSDV at 60 sources. The poor performance of DSDV can be related to the network becoming more taxed as the number of active sources grows. The EC of PIWDRA showed a moderate increase with up to 50 active sources, followed by a sharp decline at 60 sources.

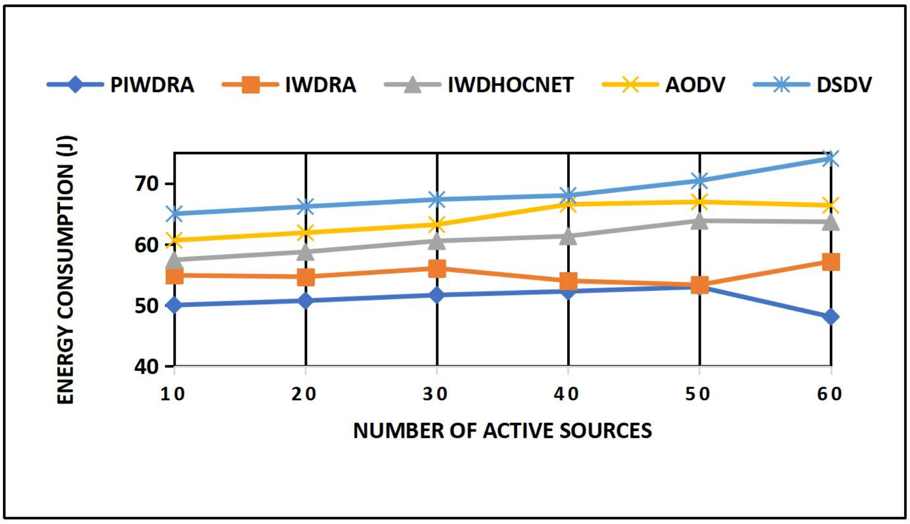

Figure 9. Energy Consumption Under Various Number of Active Sources

Network Lifetime

Figure 10 displays the relationship between network lifetime and the varying number of active sources. PIWDRA had the highest average performance of 769.02 seconds, while DSDV had the lowest average performance of 443.74 seconds. The IR (in seconds) of PIWDRA over IWDRA, IWDHocNet, AODV, and DSDV are 80.46, 174.55, 184.26 and 325.28, respectively. The highest NL of 870.8 seconds occurred with PIWDRA with 10 active sources, while the lowest NL of 330.12 seconds occurred with DSDV with 60 sources. The NL performances of the five strategies declined when the number of sources increased from 10 to 50. However, when the number of active sources is increased from 50 to 60, IWDHocNet, AODV, and DSDV experience a slight decline against PIWDRA and IWDRA, which had an upsurge.

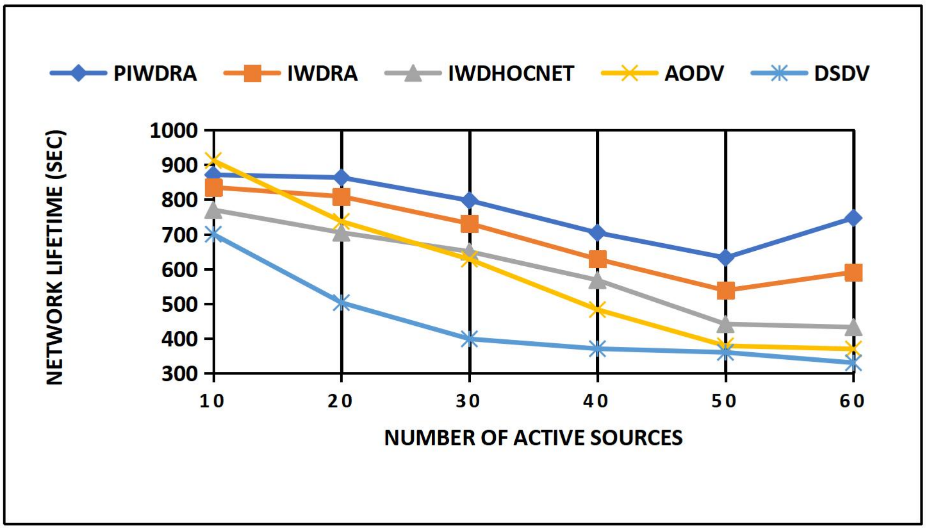

Figure 10. Network Lifetime Under Various Number of Active Sources

Table 1. Average Performance Results

Scenario 1						**Scenario 2**					
Pause Times (sec)	**Packet Delivery Ratio (PDR) in Percent (%)**					**Number of Active Sources**	**Packet Delivery Ratio (PDR) in Percent (%)**				
	PIWDRA	**IWDRA**	**IWDH-OCNET**	**AODV**	**DSDV**		**PIWDRA**	**IWDRA**	**IWDH-OCNET**	**AODV**	**DSDV**
0	95.2	93.1	82.73	77.31	73.8	10	99.83	99.64	99.03	98.82	98.75
40	93.01	90.02	85.91	74.01	65.12	20	99.43	99.25	99	98.32	98
80	91.39	89.22	86.73	72.09	69.4	30	99.55	99.39	98.76	98.35	97.21
120	91.45	88.5	85.33	74.44	70.08	40	99.3	98.16	98.57	98.22	97.72
160	93.12	89.17	85.81	75.3	71.4	50	99.59	98.81	98.63	98.41	97.84
200	93.25	89.17	87.97	79.35	60.5	60	98.25	98.78	98.07	97.64	97.47
Pause Times (sec)	**Average End-to-End Delay (AE2ED) in Seconds (Sec)**					**Number of Active Sources**	**Average End-to-End Delay (AE2ED) in Seconds (Sec)**				
	PIWDRA	**IWDRA**	**IWDH-OCNET**	**AODV**	**DSDV**		**PIWDRA**	**IWDRA**	**IWDH-OCNET**	**AODV**	**DSDV**
0	0.13	0.15	0.18	0.25	0.45	10	0.09	0.14	0.17	0.21	0.19
40	0.15	0.18	0.2	0.28	0.39	20	0.11	0.17	0.19	0.22	0.24
80	0.16	0.18	0.21	0.25	0.3	30	0.12	0.18	0.23	0.25	0.28
120	0.16	0.19	0.24	0.21	0.26	40	0.16	0.19	0.27	0.29	0.35
160	0.16	0.19	0.23	0.22	0.25	50	0.12	0.17	0.24	0.26	0.32
200	0.13	0.14	0.2	0.18	0.22	60	0.24	0.29	0.33	0.38	0.48
Pause Times (sec)	**Energy Consumption (EC) in Joules (J)**					**Number of Active Sources**	**Energy Consumption (EC) in Joules (J)**				
	PIWDRA	**IWDRA**	**IWDH-OCNET**	**AODV**	**DSDV**		**PIWDRA**	**IWDRA**	**IWDH-OCNET**	**AODV**	**DSDV**
0	22.11	29.6	36.9	47.87	54.04	10	50.01	54.9	57.43	60.64	64.98
40	28.14	30.91	40.2	49.5	55.99	20	50.73	54.66	58.74	61.88	66.17
80	30.45	34.4	40.75	45	47.67	30	51.66	56.04	60.53	63.21	67.33
120	29.09	35.3	39.09	51.8	55	40	52.27	54	61.32	66.53	68
160	27.92	32	37	56.11	58	50	52.99	53.33	63.85	66.94	70.4
200	29.5	31.11	35.5	58.98	60.8	60	48.1	57.18	63.67	66.38	74.05
Pause Times (Sec)	**Network Lifetime (NL) in Seconds (Sec)**					**Number of Active Sources**	**Network Lifetime (NL) in Seconds (Sec)**				
	PIWDRA	**IWDRA**	**IWDH-OCNET**	**AODV**	**DSDV**		**PIWDRA**	**IWDRA**	**IWDH-OCNET**	**AODV**	**DSDV**
0	492.88	453.5	429.4	402.11	400	10	870.8	834.8	770.1	912	700
40	518.35	460.73	445.02	423.14	286.36	20	863.04	808.66	704.64	736.9	503.1
80	481.87	443.66	414.99	370.16	269.03	30	797.08	730.75	650.09	628.01	398.7
120	487.36	458	424.63	385.32	297	40	704.2	628.33	568.04	483.11	370.5
160	572.3	495.06	474.8	440.19	335.44	50	632.3	538.05	441.42	378.86	360.03
200	660.28	600.06	470.87	313	261.89	60	746.72	590.81	432.55	369.7	330.12

CONCLUSION

In this paper, PIWDRA is proposed and evaluated under the scenarios of variation in pause times and the number of active sources. Based on the results from the variation in pause times, the strategy demonstrates greater resilience, self-healing, and self-configuration compared to others. Also, the strategy maintains higher robustness and adaptability as the number of active sources and data sessions varies. Under both scenarios, the strategy proposed maintained the highest packet delivery ratios (PDRs), less average end-to-end delay (AE2ED), consumed significantly less energy, and achieved a higher network lifetime. This approach optimises the selection of the best path with minimal energy, making it an efficient solution for path selection in MANETs. For future work, the algorithm can be enhanced with congestion techniques such as adjusting the data transmission rate based on current network conditions, implementing an intelligent queue management strategy at nodes to prioritise critical packets and manage buffer space efficiently, and integrating congestion control mechanisms across multiple layers of the network protocol stack for more holistic management of data flow. Also, a hybrid metaheuristic approach can be the focus of future research.

ETHICAL DECLARATION

Conflict of interest: No declaration required. **Financing:** No reporting required. **Peer review:** Double anonymous peer review.

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